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Assessment of the risk of the project's contractor bankruptcy using the Partial Least Squares approach

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Abstract

The project owner or authorized entity (e.g. project manager) is at some point before the decision problem of the delegation execution professional specialist. Typically, on the services market, operates a number of contractors capable of carrying out the intended tasks, and each of them can provide different bid. Regardless of decision-maker’s structure of the contracting preferences and number of evaluation criteria, it is necessary to verify whether the selected contractor is actually capable of completing contracted tasks. Very cheap offer may e.g. one be submitted by the bidder threatened with bankruptcy, fighting for survival. Described in this paper, method for assessing the reliability of contractors based on Partial Least Squares approach is fast and effective method to classify them in terms of risk of bankruptcy. Proposed operating model has been validated on publicly available financial data of construction companies listed on the Polish Stock Exchange.

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1. Introduction

During the economic downturn a growing number of bankrupt companies is observed. It's reason due to the non-revenue generating contracts with the need to incur the fixed costs of maintaining capacity, delays in payment for loss of liquidity and insolvency of customers, resulting in a lack of payment for the order or the products delivered. Failure to pay for the contractor is in the best case, the need for temporary financing funds from other sources, at the expense of the use of debt financing or destination of their income from other contracts to cover costs already incurred manufacture of a product or completion of the service that is not covered by the customer. On the other hand, the project owner or the general contractor is exposed to the risk of bankruptcy of its subcontractors. In this case, the money involved in the project in the form of an advance or partial payments made yet are usually very difficult to recover. Depending on the legal structure of the contract, owner of the project may also be forced to settle certain liabilities incurred by the bankrupt contractor for the project. Another problem is the suspension of the work on the project, resulting in the need to secure yet realized the extent the selection of a new contractor, sometimes changing technology and project parameters.

The problem of contractors pre-selection has been recognized and supported by optimization methods based on different classes of models. El-Sawalhi *et al*. [3] Made a review and pointed out the following:

- Dimensional Weighting Aggregation (DWA)
- Knowledge Based System (KBS),
- Multi-attriubute Analysis (MAA),
- Fuzzy set Pre-qualification,
- PERT model for contractor pre-qualifiaction,
- Analytical Hierarchy Process (AHP),
- Multi-attribute utility,
- Case-based reasoning
- Artificial Neural Networks (ANN)

In this review El-Sawalhi *et al.* [3] indicate main model's advantages, disadvantages and compare them in terms of applicability to group decision making, non-linear behavior, deal with subjective judgment, deal with both qualitative and quantitative criteria, simultaneous Multi-criteria decision making, concern of uncertainty and risk, adaptiveness, needs of system training and high knowledge of the user, understanding the mathematical behavior, and results interpretation ability. Based on this comparison, it can be stated that user expectations in the highest degree meet models based on the methods of Artificial Neural Networks and fuzzy sets. The ANN approach disadvantages came from the need of system training (here it is necessary to remember than in repeated evaluations of the same market players with unchanged selection criteria system needs be learned only once at the beginning), understanding of mathematical behavior and results interpretation. The negative impact of this last two features may be minimized by using the simple classification rule assigning bidders into clear and easy to understand classes (e.g. reliable and non-reliable companies). The unified criterion of "reliability" must be aggregated on the basis of several criteria, where values are clear and accessible for all bidders. Different sets of criteria are defined by several authors. El-Sawalhi *et al.* [3] proposed 31 attributes grouped in seven classes (financial stability, management and technical ability, experience, historical non-performance, resources, quality, health and safety). Shen *et al.* [10] focuses on social influence and technical ability group of criteria to calculate the total competitiveness value. Lam and Yu [7] indicate scoring standard for three quantitative criteria (human resource, financial strength, current workload) and eight qualitative (equipment resources, environmental considerations, claims history, management capacity, quality management potentials, safety and health aspects, past experience and past performance) criteria for their Decision Support System. Palaneeswaran and Kumaratswamy [8] proposed ten criteria in three groups (responsiveness, responsibility, competency) for construction projects. The PMI (Project Management Institute) standard PMBoK Guide [9] introduces the "Evaluation Criteria" as a result (output) of contract planning process on the basis of “Procurement Management Plan”, “Contract Statement of Work”, “Make-or-Buy Decisions” and “Project Management Plan”, processed by “Standard Forms” and “Expert Judgment” techniques. PMI introduces also a process “Request Seller Responses” with an output “Qualified Sellers List”, but it is created on the basis of “Organizational Process Assets”, “Procurement Management Plan” and “Procurement Documents only”, not concerning the “Evaluation Criteria”.

In this paper we propose the classification method allows to rapid and efficient bidders assignment to individually defined classes, generally designated as "qualified contractor" and "non-qualified contractor". It does not impose eligibility criteria, while maintaining compliance with both the observations of previously cited authors, as well as a very general procedure described in the PMBoK Guide.

2. Methodology

Feature extraction and classification are the basic methods used to analyze and interpret. The dataset coming from the economic and financial reports contains vectors of features, belonging to certain classes. These vectors are called samples. However, the number of samples is usually much smaller than the number of features. In this situation the small number of samples makes it impossible to estimate the classifier parameters properly and the classification results may, therefore, be inadequate. In literature this phenomenon is known as the Curse of Dimensionality. In this case it is important to decrease the dimension of the feature space. This can be done either by feature selection or feature extraction.

Let us assume that we have the L-classes classification problem and let $(x_i, y_i) \in X \times Y, x = \left(x_1, ..., x_p\right) \in \mathrm{R}^p$ where matrix of sample vectors X and response matrix Y are given by the following formulas:

$$X = \begin{bmatrix} x_{11} & \dots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \dots & x_{np} \end{bmatrix}, \quad Y = \begin{bmatrix} 1 & 0 & \dots & \dots & 0 \\ \vdots & & & & \vdots \\ 0 & 0 & \dots & 0 & 1 \end{bmatrix}. \tag{1}$$

Each row of the matrix Y contain 1 in a position denoting the class label.

2.1. Partial Least Squares

One of the commonly used feature extraction methods is the Partial Least Squares (PLS) Method introduced by H. Wold in 1975 (see [11]). PLS makes use of the least squares regression method in the calculation of loadings, scores and regression coefficients (see [6]). The idea behind the classic PLS s to optimize the following objective function:

$$(w_k, q_k) = \operatorname{argmax}_{w^T w = 1; q^T q = 1} \operatorname{cov}\left(X_{k-1} w, Y_{k-1} q\right) \tag{2}$$

under the following conditions:

$$w_k^T w_k = q_k q_k^T = 1 \text{ for } 1 \le k \le d, \tag{3}$$

$$t_k^T t_j = w_k^T X_{k-1}^T X_{j-1} w_j = 0 \text{ for } k \ne j, \tag{4}$$

where $\operatorname{cov}(X_{k-1}w, Y_{k-1}q)$ between $X_{k-1}w$ and $Y_{j-1}q$, vector t_k is the k-th extracted component, w_k is the vector of weights for k-th component, d denotes the number of extracted components, X_k, Y_k arise from X_{k-1}, Y_{k-1} by removing the k-th component by the following formulas:

$$X_{(k+1)} = X_k - t_k t_k^T X_k \tag{5}$$

$$Y_{(k+1)} = Y_k - t_k t_k^T Y_k \tag{6}$$

This is the so called deflation technique. It can proved that the extracted vector w_k corresponds to the eigenvector connected with the largest eigenvalue of the following eigenproblem:

$$X_{k-1}^T Y_{k-1} Y_{k-1}^T X_{k-1} w_k = \lambda w_k \tag{7}$$

Let S_B denote the between scatter matrix and S_W within scatter matrix respectively. It means that they are given by

$$S_B = \sum_{i=1}^{L} p_i \left(M_i - M_0\right)\left(M_i - M_0\right)^T, \tag{8}$$

$$S_W = \sum_{i=1}^{L} p_i E\left[\left(X - M_i\right)\left(X - M_i\right)^T \mid C_i\right] = \sum_{i=1}^{L} p_i S_i, (1) \tag{9}$$

where S_i is the covariance matrix, p_i is a-priori probability of the appearance of the i-th class, M_i is the mean vector for the i-th class and M_0 is given by:

$$M_0 = \sum_{i=1}^{L} p_i M_i. \tag{10}$$

These matrices are often used in the literature to define separation criteria. By separation criteria we mean the nonparametric function for evaluating and optimizing the separation between classes. For the PLS maximizing a separation criterion is used to find such vectors of weights that provide an optimal separation between classes in the projected space. It can be proved that for the matrix Y and the normalized input data matrix X the following property:

$$X^T Y Y^T X = \sum_{i=1}^{L} n_i^2 \left(M_i - M_0\right)\left(M_i - M_0\right)^T \tag{11}$$

holds. This mean that for PLS the matrix is almost identical with the between class scatter matrix. These eigenvector are used as vectors of weight for providing the appropriate separation. Hence we can say that the separation criterion in the PLS method is only based on the between scatter matrix. The disadvantage of the classic PLS method is that it does not give a proper separation between classes, particularly when the dataset is nonlinearly separated and the features are highly correlated. To provide a better separation between classes we propose a new weighted separation criterion. The new weighted separation criterion is used to design an extraction algorithm, based on the classic PLS method.

2.2. Weighted Separation Criterion

Let us assume that we want to find a coefficient w which separates classes the best. The existing separation criteria described in literature have some disadvantages. Some of them cannot be applied if the within scatter matrix is singular due to a small number of samples. For others the computational cost is high. In practice there are situations in which the distance between classes is small. In this case it is more important to increase the distance between classes than to decrease the distance between samples within a class, hence the influence of components denoting between and within scatters for classes is important. In this paper we propose a modified version of weighted separation criterion (see [1]), which we call the Weighted Criterion of Difference Scatter Matrices (WCDSM). Our new criterion is denoted by:

$$J = \mathrm{tr}\left(\gamma_1 S_B - \gamma_2 S_W\right) \tag{12}$$

where γ_1, γ_2 are parameter, S_B and S_W are between scatter matrix and within scatter matrix respectively.

Applying a linear transformation criterion, condition (12) can be rewritten in the more suitable for optimization form:

$$J(w) = \mathrm{tr}\left(w^T \left(\gamma_1 S_B - \gamma_2 S_W\right) w\right) \tag{13}$$

By using the Lagrange multipliers method we optimize the following criterion:

$$\max_{w_k} \sum_{k=1}^{d} w_k^T \left(\gamma_1 S_B - \gamma_2 S_W\right) w_k, \tag{14}$$

under the following conditions:

$$w_k^T w_k = 1 \quad \text{for } 1 \le k \le p. \tag{15}$$

To find the correct value of the parameter γ we used the following metric:

$$\rho(C_1, C_2) = \min_{c_1 \in C_1, c_2 \in C_2} \rho(c_1, c_2), \tag{16}$$

where C_i is the i-th class, for $i \in \{1,2\}$ and $\rho(c_1, c_2)$ is the distance between samples c_1 and c_2. The value of the parameters γ_1 and γ_2 was chosen by the using the following formula:

$$\gamma_1 = \frac{\rho(M_1, M_2) - \min\left\{\rho(C_1, C_2)\right\}}{\rho(M_1, M_2)}, \; \gamma_2 = 1 - \gamma_1 \tag{17}$$

Such a parameter γ_2 equals 0 if and only if certain i and j classes exist for which $\rho(C_i, C_j) = 0$. This means that at least one sample which belongs to classes C_i and C_j exist. If distance between classes increase, the value of γ also increases. Therefore the importance of the component S_W becomes greater.

2.3. Extraction Method

In this section we will apply a new weighted separation criterion to design a extraction algorithm based on PLS. The idea of the new extraction algorithm is to optimize the objective criterion

$$w_k = \arg\max_w \left(w^T (\gamma_1 S_B - \gamma_2 S_W) w \right), \tag{18}$$

under the following conditions:

$$w_k^T w_k = 1 \quad \text{for } 1 \le k \le d \tag{19}$$

$$t_k^T t_j = w_k^T X_{k-1}^T X_{j-1} w_j = 0 \quad \text{for } k \ne j, \tag{20}$$

where d is the number of extracted components. We shall call this extraction algorithm - Extraction by applying Weighted Criterion of Difference Scatter Matrices (EWCDSM). It can proved that the extracted vector w_k corresponds to the eigenvector connected with the largest eigenvalue for the following eigenproblem:

$$(\gamma_1 S_B - \gamma_2 S_W) w = \lambda w. \tag{21}$$

Also, the k-th component corresponds to the eigenvector related to with the largest eigenvector for the following eigenproblem:

$$X_{k-1} X_{k-1}^T \left((\gamma_1 + \gamma_2) D - \gamma_2 I \right) t = \lambda t. \tag{22}$$

Matrix $D = [D_j]$ is an $n \times n$ block-diagonal matrix where D_j is a matrix in which all elements equals $1/nn_j$, n_j is the number of samples in the *j*-th class, I is identity matrix.

2.4. Classification

Let us assume that X_{train} and X_{test} are the realizations of the matrix X for train and test datasets respectively.

The idea of a training step is to extract vectors of weights w_k and components t_k by using the train matrix X_{train} and to store them as a column in matrices W and T respectively. In order to classify samples into classes we use train matrix X_{train} to compute the regression coefficients by using the least squares method [6] given by:

$$Q = W \left(P^T W \right)^{-1} U^T, \tag{23}$$

where,

$$U = YY^T T \left(T^T T \right)^{-1}, \tag{24}$$

$$W = X^T U, \tag{25}$$

$$P = X^T T \left(T^T T\right)^{-1}. \tag{26}$$

Then we multiply test matrix X_{test} by the coefficients of the matrix Q. In order to classify samples, corresponding to the Y_{test} matrix, we use the decision rule:

$$y_i = \arg\max_{j=1,\dots,L} Y_{test}(i,j). \tag{27}$$

The final form of the response matrix is the following:

$$Y_{test} = \left[y_1 y_2 \cdots y_L\right]^T. \tag{28}$$

3. Experiments

3.1. Dataset

We applied the new extraction method to the economic data taken from 17 construction companies. All of them are listed on the Polish stock exchange (see [12]). Each company is represented by one feature vector. We take the following seventeen indicators: Price/Earnings Ratio (P/E), Price/BookValue (P/BV), Net Incomes, Gross Incomess, Incomes from sales, Net Profit, Net cash flow (operational activities) Net cash flow (investing activities), assets, commitments and reserve for feature commitments, long-term commitments, short-term commitments, Equity Capital, Share Capital, Book value per share (BV/S), Earnings per share and number of shares issued. The value of all indicators are listed in the Table 1 and Table 2.

Table 1. Indicators for construction companies (in thousand PLN)

indicator	Budimex	Polimex-Mostostal	Mostostal Zabrze	Mostostal Export	Mirbud	Mostostal Płock	Energopol Południe	Unibep	Erbud
Price/Earnings Ratio (P/E)	14,71	-5,05	23,38	-0,64	6,54	-3,45	31,74	14,93	-7,35
Price/BookValue (P/BV)	3,58	1,19	1,14	0,82	0,74	0,52	1,74	1,12	0,81
Net Incomes	5019669,0	3622392,0	335094,0	33344,0	408562,0	97860,0	94265,0	934182,0	1245578,0
Gross Incomes	280280,0	-188691,0	-5286,0	-43891,0	30854,0	-12225,0	1655,0	22549,0	-21791,0
Incomes from Sales	154928,0	-211406,0	10022,0	-46579,0	28150,0	-9922,0	3742,0	20637,0	-28122,0
Net profit	132732,0	-171451,0	8163,0	-46595,0	22716,0	-8397,0	2553,0	13556,0	-25284,0
Net cash flow (operational activities)	230748,0	47892,0	-42744,0	-12085,0	57712,0	-7380,0	15176,0	43152,0	-61917,0
Net cash flow (investment	-170617,0	-88865,0	-4386,0	2700,0	-31483,0	4111,0	1047,0	-34465,0	-14434,0

activities)									
Assets	3818630,0	3156393,0	298482,0	76645,0	441706,0	93846,0	91837,0	480253,0	682744,0
commitments and reserve for feature commitments	3273306,0	2433901,0	132024,0	40079,0	240466,0	37953,0	45244,0	299501,0	453525,0
long-term commitments	33652,0	249904,0	9624,0	973,0	51858,0	3136,0	6237,0	58004,0	56537,0
short-term commitments	1792443,0	2183997,0	122400,0	39106,0	178439,0	27794,0	39007,0	241497,0	324560,0
Equity Capital	545324,0	722492,0	166458,0	36566,0	201240,0	55893,0	46593,0	180752,0	229219,0
Share Capital	127650,0	20846,0	149131,0	79610,0	75000,0	20000,0	44400,0	3402,0	12644,0
Book value per share (BV/S) (in PLN)	21,36	1,39	1,12	0,82	2,68	27,95	4,20	5,31	18,13
Earnings per share (in PLN)	5,20	-0,33	0,06	-1,05	0,30	-4,20	0,23	0,40	-2,00
Number of shares (thousands)	25530	521154,00	149131	44559	75000	2000	11100	34022	12644

Table 2. Indicators for construction companies (in thousand PLN) continued

indicator	Energomontaż Południe	Awbud	ABM Solid	Hydrobudowa Polska	PBG	Budus	DSS	Mostostal Warszawa
Price/Earnings Ratio (P/E)	-6,47	14,72	-0,30	-8,29	10,93	-10,20	-0,13	-2,61
Price/BookValue (P/BV)	1,38	0,92	0,32	0,19	0,82	2,18	-0,19	1,36
Net Incomes	327961,0	221093,0	415335,0	1234102,0	964135,0	379728,0	483152,0	2548500,0
Gross Incomes	-20479,0	5208,0	-34179,0	-803,0	180325,0	-3858,0	535674,0	-157771,0
Incomes from Sales	-29951,0	8990,0	-49730,0	-18450,0	116970,0	-15112,0	-697174,0	-149380,0
Net profit	-20471,0	9743,0	-42684,0	-18540,0	92891,0	-11924,0	-679309,0	-122788,0
Net cash flow (operational activities)	18253,0	-2635,0	-12022,0	-14623,0	-40858,0	5320,0	-14744,0	-192808,0
Net cash flow (investment activities)	-6359,0	-1252,0	-2131,0	-45897,0	-402166,0	-15242,0	-128553,0	15269,0
Assets	388984,0	242968,0	276720,0	1568574,0	2929963,0	379299,0	302908,0	1333264,0
commitments and reserve for feature	292260,0	87315,0	237072,0	751929,0	1691825,0	323740,0	783971,0	1097912,0

commitments								
long-term commitments	69891,0	2737,0	36344,0	22712,0	502393,0	30428,0	4873,0	70382,0
short-term commitments	222369,0	84578,0	200728,0	729217,0	1189432,0	272736,0	779098,0	1027530,0
Equity Capital	96724,0	155653,0	39648,0	816645,0	1189432,0	55829,0	-481063,0	235352,0
Share Capital	92307,0	82429,0	3412,0	210558,0	1238138,0	2433,0	51607,0	44801,0
Book value per share (BV/S) (in PLN)	1,36	1,89	5,00	3,88	86,61	7,57	-37,21	11,77
Earnings per share (in PLN)	-0,29	0,12	-5,38	-0,09	6,50	-1,62	-52,55	-6,14
Number of shares (thousands)	70792	82429	7935	210558	14295	7371	12928	20000

The dataset was randomly divided into train and test datasets. The train dataset contains indicators taken form the annual financial statement (2011) for 12 companies such as Budimex, Polimex Mostostal, Mostostal Zabrze, Mostostal Export, Mirbud, Mostostal Płock, Energopol Południe, Unibep, Energomontaż Południe, Awbud, Hydrobudowa Polska, ABM Solid. The test dataset contains indicators taken from the annual financial statement (2011) for next 5 companies such as Mostostal Warszawa, Erbud, PBG, Budus, DSS. Each of samples in train and test dataset belongs into one of two classes of risk of bankruptcy: not at risk and at risk of bankruptcy. In 2012 Six construction companies listed on Polish stock exchange, that is Polimex-Mostostal, PBG, Hydrobudowa, Budus, DSS, AMB Solid, bankrupt. Three of these companies, that is Polimex-Mostostal, AMB Solid and Hydrobudowa belongs to train dataset. Rest of them, that is PBG, Budus, DSS belongs to test dataset.

3.2. Classification Performance

In order to examine the classification performance of EWCDSM we use the following experimental scheme. First each dataset is normalized. Using the algorithm described in sections 2.2 and 2.3 we carried out the procedure for learning classifier on train dataset containing 12 construction companies. As a result we received a matrix of components. Then this matrix is used to test the efficiency of the classifier on the test dataset. As a result we receive the assignment of company into class of risk of bankruptcy. Classification performance is computed by dividing the number of samples classified properly by the total number of samples. This rate is known as a standard error rate [2]. We examine classification performance for different numbers of components. Appropriate number of components is $d = 11$. For such number of components the classification performance equals 100%. It means that all five companies from test dataset were classified properly. Three of them, that is PBG, Budus, DSS, bankrupt in 2012. Mostostal Warszawa and Erbud were not at risk of bankruptcy in 2012. The same procedure was used for classification using PLS method. In this case one of companies which was not at risk of bankruptcy was marked as a company at risk of bankruptcy. The classification performances for both PLS and EWCDSM are listed in Table 3.

Table 3. Classification performance (per cent)

PLS	EWCDSM
80.00	100.00

4. Conclusions

We have introduced a new linear and nonlinear version of an algorithm for feature extraction. Our algorithm uses a new weighted separation criterion to find the weights vector which allows for the scatter between the classes to be maximal and for the scatter within the class to be minimal. The new extraction algorithm can distinguish between company at risk of bankruptcy for economic data coming from stock exchange. Moreover, we have shown that the classification performance of the proposed algorithm was significantly higher for our method than for classical the PLS method.

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